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resistivity and porosity are obtained from well logs. Formation water resistivity can be obtained from the spontaneous potential log readings, but in most cases, it needs an empiric determination for each well. Cementation exponent is derived from the linear fit between resistivity and porosity and, normally, it is rock dependent and needs to be determined in core analysis. Saturation exponent exhibits constant behavior and independent of lithology, as point out by Archie (Archie, 1942) and in good approximation, may be considered equal to two (Ellis, 1985).

In many practical situations, there is a good confidence in porosity estimated from porosity logs, mainly for clean water-bearing formations. However, there is not the same confidence about formation water resistivity and cementation exponent. Formation water resistivity is measured in fluid samples at formation temperature; unfortunately, this kind of sample is not always available. Cementation exponent is the slope of the line, in a log-log plot, which fits the porosity and rock resistivity measured in core samples 100% water saturated. (Darling, 2005).

Picket plot is a well-established method presenting a graphic solution for the Archie's equation (Pickett, 1966), which produces an estimate of water saturation, when formation water resistivity and cementation exponent are unknown.

We introduce a new competitive neural network specialized to find statically relevant angular patterns in the input data. This characteristic of angular competitive neural network permits the realization of angular pattern recognition in the Pickett plot to determine, simultaneously, water resistivity and cementation exponent.

Our goal here is to reduce the inherent imprecision in the visual interpretation of Pickett plot and to produce a more realistic estimate of water saturation. The evaluation of this method is accomplished on synthetic data and actual wireline logging data.

Methodology

In a quick look formation evaluation is the common practice, the adoption of fixed values for Archie`s exponents, as shown in Table 1.

Table 1 - Usual values for Archie's exponents

Rock	Archie's exponents	
	m	n
Sandstones	2,15	2,00
	2,00	2,00
Carbonates	2,00	2,00

Pickett plot

Dick Pickett (Pickett, 1966) developed a graphic method to solve the Archie's equation producing an estimate for formation water resistivity and cementation exponent. Pickett rewrites the Archie's equation considering the saturation exponent (n) equal to 2 and takes the logarithm on both sides of Archie equation, in the form.

$$log\, R_t = -m log\, \phi + log\left(\frac{R_w}{S_w^n}\right) \quad (1)$$

ϕ represents porosity. S_w is the water saturation. m is the cementation exponent and R_w is the formation water resistivity. In a log-log paper, equation 1 describes a family of lines with slope equal to cementation exponent.

All points with unit water saturation describe one particular straight line called as water line, as point out in Figure 1. The slope of water line is the cementation exponent and the water resistivity, at formation temperature, is determined by the intersection of water line and a vertical on 100% porosity, as shown in Figure 1.

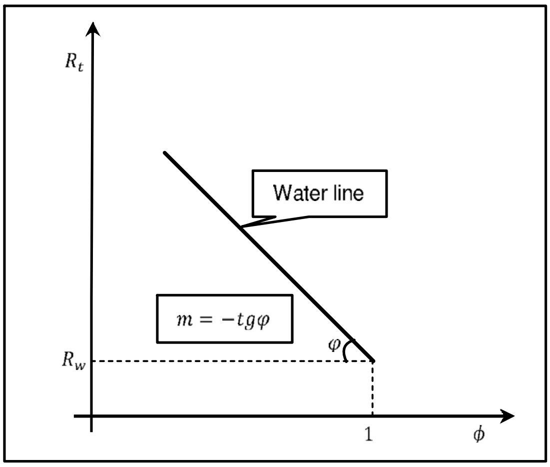

Figure 1 – Pickett plot. Water resistivity and tortuosity factor determination.

Plotting in a log-log paper a depth interval, with porosity in the abscissas and deep resistivity log readings in the ordinates, one defines a set of points in the Pickett plot, showed as red circles in Figure 2.

Defined the water line, showed in blue in Figure 2-A, can drawn parallel lines, in the northeast direction, representing values of water saturation less than unit, as shown in the Figure 2-B.

Pickett plot as any graphic method is subject to visual misinterpretation and deeply dependent of interpreter expertise. To reduce the misinterpretation, we introduce a new architecture of competitive neural network to solve Pickett plot.

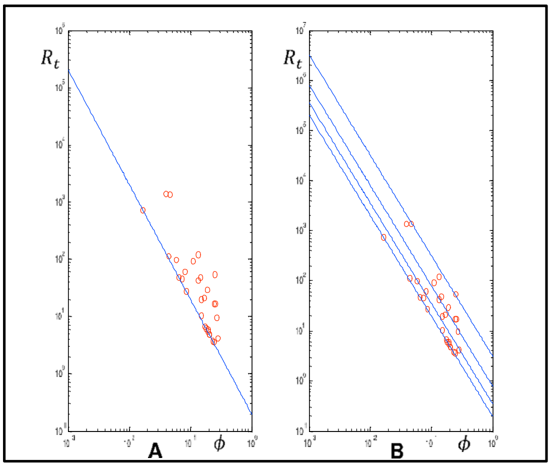

Figure 2 – A- Water line in blue.
B- Water saturation scale.

Competitive Neural Network

Competitive neural network is characterized by a single competitive layer, where their neurons compete among them, such that, only one neuron is active at a time. This characteristic turns the competitive neural network appropriated to extract statistic characteristics, in terms of the geometric distribution of input data.

Different of any other artificial neural network, the output of a competitive network has no interest. The useful result can be the position in the competitive layer or the weights of winner neuron.

A typical architecture of competitive neural network is shown in figure 3.

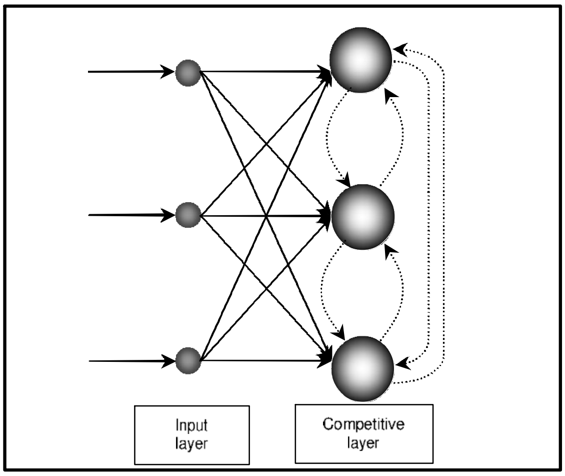

Figure 3 – The architecture of competitive neural network.

We introduce a new competitive neural network, called as angular competitive neural network, specialized for the extraction of statistically relevant angular patterns presents in the input data. This characteristic may be used to promote a classification of input data, second an established criterion.

The estimate of water saturation requires the correct location of water line in the Pickett plot. The water line can be interpreted as a particular angular pattern presented by the points 100% water saturated, considering the water-bearing interval sufficiently sampled, these points when drawn in the Pickett plot will exhibit an angular pattern that identifies the position of water line. This is the premise that governs the rule of competition of angular competitive neural network.

Angular Competitive Neural Network

The architecture of angular competitive network is composed by three layers: the input layer, the competitive layer and one intermediate layer, the selective layer, as shown in Figure 4.

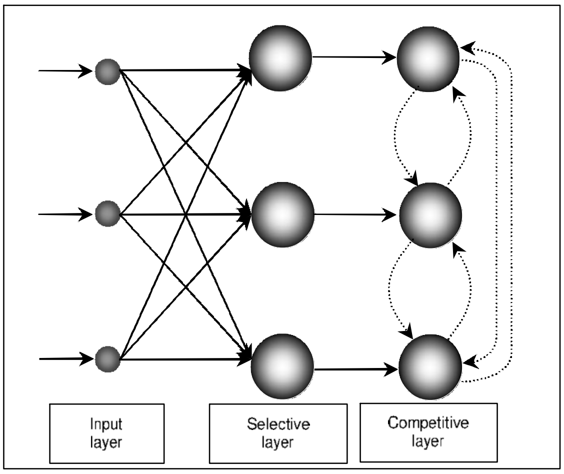

Figure 4 – Architecture of angular competitive neural network.

Each training set defines dynamically the number of neurons in the selective layer and in the competitive layer.

The selective layer operates to promote the selection of input data. A special activation function defines the selection criterion that acts in the sense of allowing or not the production of an effective output. Each selective neuron represents a point of training set or one column of weight matrix.

The competitive layer acts exactly as a classical competitive layer, promoting a competition among their neurons and allowing that only one of them wins the competition and produce the layer output.

Training set is the subset of input data used to determinate the weight matrix. Points in the Pickett plot with the smallest resistivities values form the training set. These points are natural candidates to represent water-bearing formation.

The learning process of angular competitive neural network associates each point in the training set to a position vector and calculates the unitary vectors resulting of the subtraction of one position vector by all the others.

The weight matrix between the input and selective layers is defined in a convenient form to storage the coordinate pair of each unitary difference vector as complex number, with the abscissa (ϕ) as real part and the ordinate (R_t) as imaginary part. This square complex matrix has order equal to the number of points in the training set and null diagonal.

The input data in the angular competitive network will be formed by the resulting of the subtraction of each position vector in the Pickett plot for each one in the training set, as shown in Figure 5.

We take the unitary vector of each difference vector. The form of storage of this unitary difference vectors is equal to the form used for the weight matrix as an element of a complex matrix. This global difference matrix has a number of rows equal to the number of neurons in the input layer and a number of columns equal to the number of points in the Pickett plot.

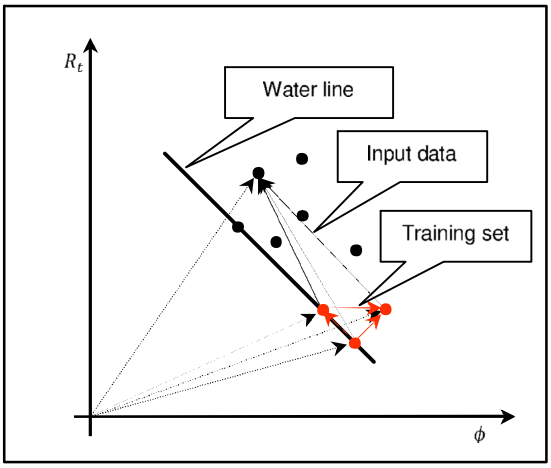

Figure 5 – Input data and training set of angular competitive network.

For each time step, a row of the global difference matrix is presented to the input layer. The operation accomplished in each selective neuron results in the input potential (u) corresponding to the real part of the complex product of each element in the input vector (column of the global difference matrix) and the complex conjugated of each element of the weight vector (column of the weight matrix). This operation is to take the cosine of the angle between the unitary difference vectors. The condition for two vectors have the same direction is the cosine of angle formed is equal to 1 or -1. The activation function for each selective neuron verifies the occurrence of input potential in the intervals [-1 -0.98] or [0.98 1] producing an output equal to the unit, as shown in Figure 6.

The selective layer is activated by only one neuron of the input layer and it produces a binary vector as output that is passed to the competitive layer. Each neuron in the output layer produces a sum of the number of times that its linked neuron in the selective layer was activated. After the presentation of all the columns of global difference matrix, the neurons in the output layer compete among them. The winner neuron is that one linked to the selective neuron with the largest number of activations.

The location of water line in the Pickett plot performed by angular competitive neural network assumes two premises. The first supposes the presence of at less two water-bearing points in the training set. The second considers that water-bearing interval has a sufficient number of sampled points.

The position of the water line is associated to the winner neuron in the competitive layer. Let be *k* the position of the winner neuron, this indicates that in the direction of the difference vector *k* corresponding to the *k* element of the training set is the one with the largest number of align points, this defines the direction of water line by the *k* point in the Pickett plot.

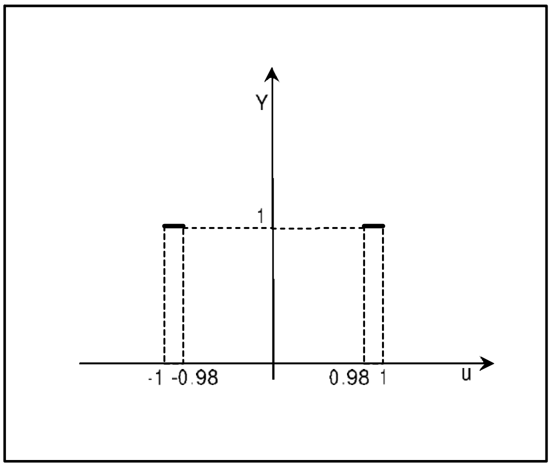

Figure 6 – Activation function. u is the input potential. Y is the neuron output.

Results

The ability of angular competitive neural network to interpret the Pickett plot is evaluated with synthetic resistivity log obtained from the Archie's equation with random values for porosity in the interval [0.05, 0.3], for water saturation in the interval [0.05, 0.8]. Formation water is equal to 0.2 *ohm.m* and cementation exponent is taken equal 2.0.

Figure 7 shows the Pickett plot with the set of synthetic points represented by red circles and the exactly water line in red.

Figure 8 shows in blue circles the chosen training set and in blue, the water line. The straight line defined by angular competitive neural network is coincident with the exactly water line. It can be observed that even in the presence of noise data, the angular competitive network was robust to obtain the correct location of the water line.

Figure 9 shows the visual comparison among the water line obtained by the angular competitive network (line in blue) with the straight line located by linear regression on the same points used in training set. It can be observed that linear regression is unable to locate the water line.

To evaluate the competence of angular competitive neural network to locate the water line in Pickett plot with actual well logs we chose to use a published data (Darling, 2005). We show in Figure 10 this actual well log suite composed by natural gamma ray (GR), deep resistivity (Rt) and density (Rhob) as presented by Tobb Darling (Darling, 2005).

Figure 11 shows the correspondent Pickett plot, with log points in red circles. The circles in blue represent the training set. To produce this Pickett plot, we use raw deep resistivity log readings as rock resistivity. Porosity is calculated from density log, considering quartz grain density and fresh water.

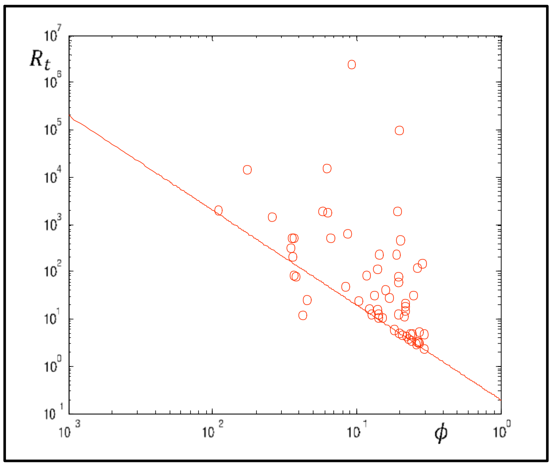

Figure 7 – Pickett plot. Synthetic data.

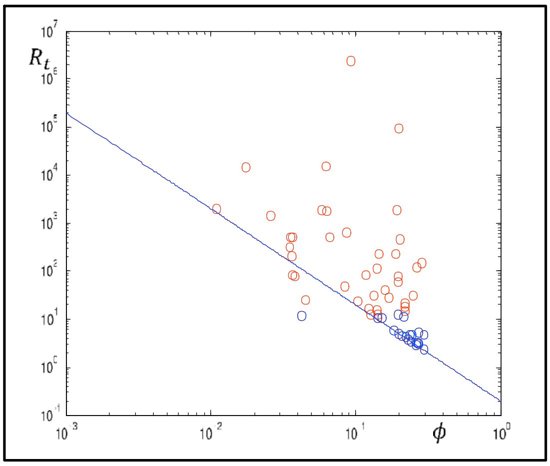

Figure 8 – Located water line in blue. Training set as blues circles.

Figure 12 shows the water line defined by angular competitive neural network represented by line in blue in comparison with water line defined by linear regression with same points of the training set. It is observed that the linear regression is unable to locate water line position as done by angular competitive network, which find the position of water line very close that one located by a log analyst, considering the information from core analysis about the fluid density and grain density.

The core information affects the calculated porosity values, which was not considered in the application of the angular competitive network. The core analysis still supplies the value of cementation exponent.

The Table 2 allows the comparison among the values of the cementation exponent obtained by three methods: core analysis, angular competitive neural network, and linear regression as well as the value of water resistivity as obtained by Tobb Darling visual interpretation (Darling, 2005), the angular competitive neural network and linear regression.

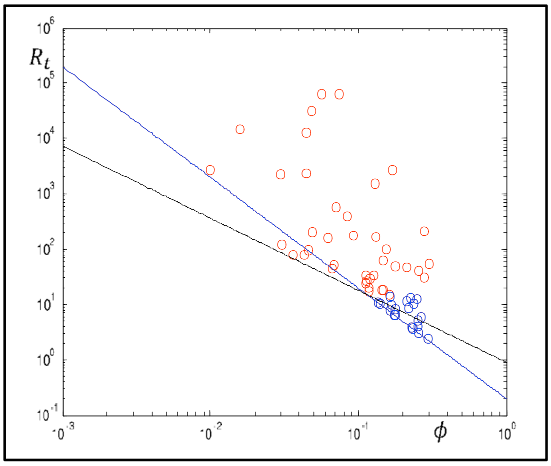

Figure 9 – Water line in black, determinate by linear regression.

Conclusions

For many geologists and petroleum engineers Pickett plot is considered as a quick look method. This kind of sense is not due to naive simplifications of the rock model or theoretical contradictions in the relationship defined in the Archie's equation, but mainly by the visual interpretation needed for the location of water line based in human expertise.

This work presents an autonomous method to interpret the Pickett plot based on an example of intelligent algorithm, the angular competitive neural network, which is able to produce a good estimate of water line location and consequently, determines the formation water resistivity at formation temperature and the cementation exponent. In this stage, all quantities involved in the Archie's equation are defined and the water saturation is straightforward.

The evaluation of this method showed an estimate of the water resistivity and cementation exponent values very close to that one obtained by direct measure in laboratory by core analysis.

The application of angular competitive neural network is not restrict to formation evaluation and may be used to solve other problems in geophysics and engineering.

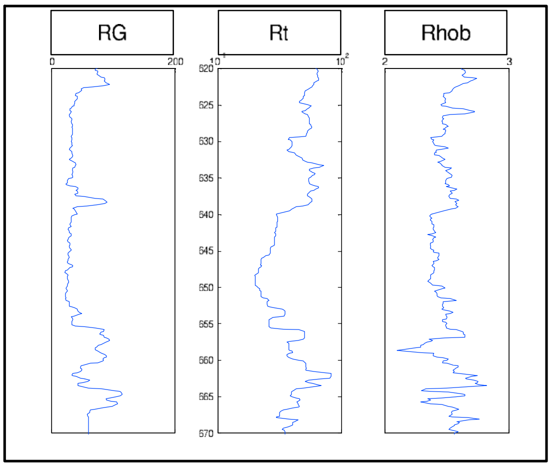

Figure 10 – Wireline logs (Darling, 2005).

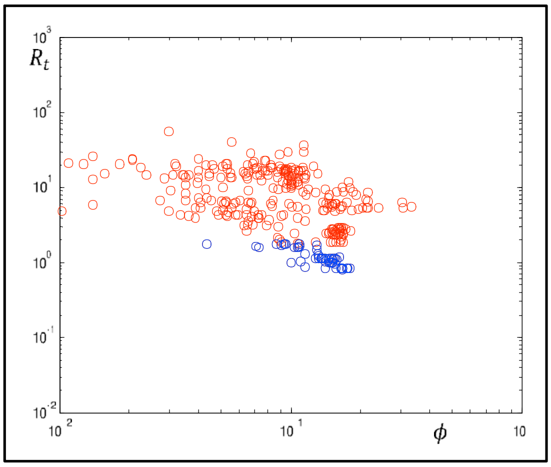

Figure 11 – Actual data as red circles. Training set as blues circles.

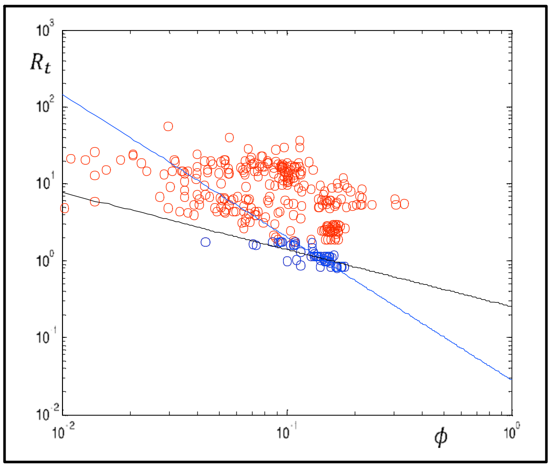

Figure 12 – Water line from angular competitive network in blue. Water line from linear regression in black

Table 2 – Formation water resistivity and cementation exponent.

Method	R_w	m
Darling (Darling, 2005)	0.025	1.9
Angular Competitive Neural Network	0.028	1.85
Linear regression	0.27	0.74

Acknowledgments

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